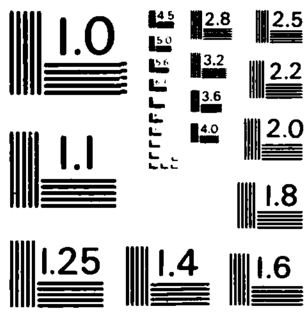
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The perceptions of risks (e.g., diseases, accidents, natural hazards) is investigated using a multi-task, multi-model approach. We studied the proximities among 18 risks induced by three tasks: judgment of similarity, conditional prediction and dimensional evaluation. The comparative judgments (similarity and prediction) were reasonably close but the dimensional evaluation did not correlate highly with either similarity or prediction. Similarity judgments and conditional predictions appear to be represented

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best by tree models, which are based on discrete features, while the dimensional evaluations are better explained by spatial models, such as multidimensional scaling and factor analysis. We discuss the implications of these results for the study of mental representation and for the analysis of risk perception.

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Representations of Perceptions of Risks

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Abstract

The perception of risks (e.g., diseases, accidents, natural hazards) is investigated using a multi-task, multi-model approach. We studied the proximities among 18 risks induced by three tasks: judgment of similarity, conditional prediction and dimensional evaluation. The comparative judgments (similarity and prediction) were reasonably close but the dimensional evaluation did not correlate highly with either similarity or prediction. Similarity judgments and conditional predictions appear to be represented best by tree models, which are based on discrete features, while the dimensional evaluations are better explained by spatial models, such as multidimensional scaling and factor analysis. We discuss the implications of these results for the study of mental representations and for the analysis of risk perception.

Much work in Cognitive Psychology is aimed at the construction of a formal representation of some domain of knowledge or behavior. These representations are commonly constructed on the basis of observed data using some appropriate statistical, geometric or computer model. At the current state of knowledge, formal representations of psychological structures are inevitably incomplete because the data usually reflect only limited aspects of the process under study and because the assumptions that underlie the representations are, at best, approximate. The use of reaction time, error rate or verbal protocols, for example, provide only a limited view of human reasoning. Analogously, the use of hierarchical clustering or multidimensional scaling to represent some semantic domain may exclude significant aspects of the data or impose extraneous features that are not present in the data. Although there are no general methods for avoiding errors of omission or commission, caused by the selection of tasks and models, these errors may sometimes be reduced by the use of a multi-task, multi-model approach that investigates the same psychological structure using different tasks and different representations. In this paper we apply this approach to the study of the perceived relations among risks.

As individuals and as a society we are constantly required to compare, evaluate and manage risks. Individuals control their smoking, dietary and driving habits; society imposes speed limits and regulates food additives, drugs and pollutants. Since the regulation and management of many risks (e.g., nuclear power, genetic engineering) are subject to an intense public debate, the

perceptions of these risks are of considerable interest for public policy, as well as for cognitive psychology. Indeed, the question of how people perceive and cope with risk has captured the attention of both natural and social scientists (e.g., Fischhoff, Slovic, Lichtenstein, Reed & Combs, 1978; Fischhoff, Lichtenstein, Slovic, Derby & Keeney, 1981; Johnson & Tversky, 1983; Hohenemser, Kates & Slovic, 1983; Slovic, Fischhoff & Lichtenstein, 1980, 1981, 1983; Rowe, 1977; Schwing & Albers, 1980; Starr, 1969; von Winterfeldt, John & Borcherding, 1981). A significant part of this research has been devoted to the construction of multivariate representations of risks based upon the judgments of experts and lay people.

The present study investigates the perceived relations among prevalent causes of death using three different types of data: judgments of similarity, conditional predictions and ratings of risks on evaluative dimensions. These data, which give rise to different measures of proximity between the risks, are used to compare three classes of representations: hierarchical and non-hierarchical trees, ordinal multidimensional scaling and principal component factor analysis. An outline of the study is presented in Figure 1.

Insert Figure 1 about here

METHOD

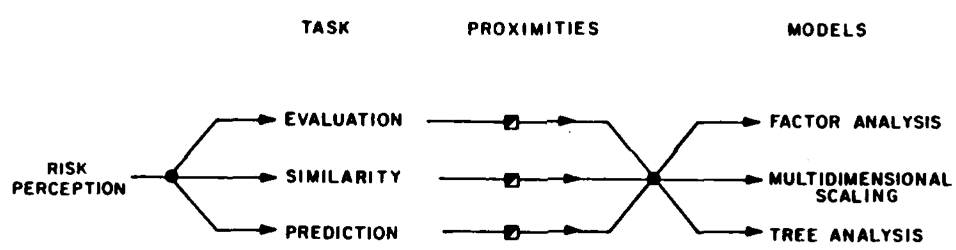


Figure 1. Schematic Representation of the Study.

Risks. The items used in this study were generated by 68 undergraduates from Stanford University who were asked to list the major risks which are primary causes of death in the U.S.in our time. The risks listed by the subjects were ranked by their frequency of mention and by the estimated number of fatalities they cause, and the 18 risks with the highest average rank were selected for study. This set included: Accidental falls, Flood, Tornado, Lightning, Electrocution, Fire, Nuclear accident, Toxic chemical spill, Homicide, Terrorism, War, Airplane accidents, Traffic accidents, Stroke, Heart disease, Lung cancer, Leukemia, Stomach cancer.

Tasks. Three tasks were used in the study:

(1) Judgment of Similarity. Subjects were presented with all pairs of risks and asked to rate each pair on a scale from 1 (very dissimilar) to 9 (very similar). The order of risks within pairs was counterbalanced and the order of the pairs was randomized.

(2) Conditional Prediction. Prior to this task all subjects estimated the number of people in the U.S. that die each year from each one of the 18 risks. Afterwards they were given the following instructions. "Suppose you were to learn that many more people die each year in the U.S. from _______ than you had estimated. Please indicate whether or not you would increase your estimate for each of the following causes of death, given this new information." Thus, the subjects were asked to judge which of the risk estimates should be increased,

assuming the target risk had been underestimated. The order of the target risks was randomized and the judged risks were presented alphabetically.

(3) Dimensional Evaluation. Following the procedure investigated by Fischhoff et al. (1978), each risk was evaluated using a 7 point rating scale, on nine dimensions, which have emerged from an analysis of the acceptability of risk (e.g., Lowrance, 1976). The nine dimensions are presented in Table 1. The risks were presented alphabetically and the order of the scales was randomized.

Insert Table 1 about here

Design. A total of 245 subjects, were recruited through an advertisement placed in the University of Oregon newspaper. Each subject was randomly assigned to one of six groups, of roughly equal size, which completed a subset of the experimental tasks. The 153 similarity judgments ((18 x 17)/2) and the 306 conditional predictions (18 x 17) were randomly divided into three equal groups; the 162 dimensional evaluations (9 scales x 18 risks) were divided into four groups. Three groups of subjects each completed one third of the similarity judgments and rated the risks on two of the scales. A fourth group rated the risks on the three remaining scales and performed one third of the conditional predictions. The two remaining groups each performed a third of the conditional predictions. Subjects participated in a number of unrelated experimental tasks and received 6 dollars for approximately one and one-half hours of their time.

Table 1: Dimensional Evaluation Scales
(after Fischhoff et al., 1978)

Not known to science

To what extent are the risks known to science?

Not known to exposed

To what extent are the risks known precisely by the persons who are exposed to those risks?

New/Unfamiliar

Is this risk new and novel or old and familiar?

Effect Delayed

To what extent is the risk of death immediate--or is death likely to occur at a later time?

Involuntary

Do people become exposed to this risk voluntarily?

Not controllable

If you are exposed to the risk, to what extent can you, by personal skill or diligence, avoid death?

Certainly Fatal

When the risk from the activity is realized in the form of a mishap or illness, how likely is it that the consequence will be fatal?

Dread

Is this a risk that people have learned to live with and can think about reasonably calmly, or is it one that people have great dread for--on the level of a gut reaction?

Catastrophic

Is this a risk that kills people one at a time (chronic risk) or a risk that kills large numbers of people at once (catastrophic risk)?

TASK ANALYSIS

Each of the three tasks employed in the present study (similarity judgment, conditional prediction and dimensional evaluation) induces a proximity relation among the risks. Similarity judgments are perhaps the simplest and most direct method of assessing the proximity of stimuli. Conditional prediction can be viewed as a judgment of covariation: the proximity between risks can be measured by the extent to which an increase in one risk produces an increase in the estimate of another. To derive a measure of proximity from the dimensional evaluation task, we can compute the correlation between the risk profiles across the nine scales.

Although all three tasks provide judgmental data about the proximity between risks, the tasks differ from each other in several important respects. First, similarity judgments and conditional predictions are both comparative; the subject compares two risks and assesses either their likeness or their covariation. In contrast, the dimensional evaluation task is non-comparative: the subject evaluates each risk separately without making explicit comparisons to other risks. Second, the dimensional evaluation measure is compositional in the sense that overall proximity between risks is defined by the correlation between their ratings. Judgments of similarity and conditional predictions are holistic in the sense that the subjects are free to identify, weigh and combine features as they see fit. Similarity, however, is based on a subjective criterion of correspondence, while prediction is based on an objective standard--the number of fatalities. Thus, the

evaluation task restricts judgment to a fixed set of global dimensions, combining them according to a well-defined rule, while the comparative tasks do not constrain either the set of attributes or the composition rule.

This analysis suggests that the three tasks may tap different aspects of people's knowledge about risk and give rise to distinct proximity relations that call for different formal representations. More specifically, risks can be compared in terms of a few global dimensions or they can be compared in terms of specific or local features. In the former mode of comparison, all risks are judged relative to the same attributes, while in the latter the set of relevant features may vary from one comparison to another. For example, all risks can be evaluated in terms of the immediacy of the effect or the severity of the consequences. On the other hand, a feature such as radiation is probably considered in the comparison of nuclear accidents and leukemia but not in the comparison of tornado and flood. Because the evaluation task is defined in terms of global dimensions we might expect spatial models such as multidimensional scaling and factor analysis, to fit the evaluation data better than the similarity and the prediction data. On the other hand, if people compare risks in terms of their common and distinctive features (Tversky, 1977), we might expect discrete feature models to fit the similarity and the prediction data better than the dimensional evaluation data.

The preceding discussion also suggests the hypothesis that judgments of similarity and conditional predictions, which are based on the comparison of pairs, will correlate higher with each other than with the evaluation task, which

does not involve a direct comparison of risks. Thus, we expect that the nature of the task will determine, in part at least, the compatibility among the data sets and the correspondence between data and models. These hypotheses are investigated in the following section.

RESULTS

Compatibility Among Proximities

Preliminary Analysis. Data from the three tasks were used to construct three sets of proximities between all pairs of risks. For the similarity data, we simply averaged rated similarity across subjects. For conditional predictions, we defined a (symmetric) measure of proximity between risks by $[P(x|y) + P(y|x)]/2$ where $P(x|y)$ is the percentage of subjects who wished to increase their estimate of risk x when told they had underestimated risk y. For the dimensional evaluation data, we first averaged the subjects' ratings for each of the 18 risks and defined the proximity between risks by their product-moment correlation across the nine scales. As an alternative definition of the proximity between risk profiles we also computed the Euclidean distance between every pair of profiles. Since the two measures yielded similar results, we report only the correlational data. The proximities derived from the similarity and the prediction data are presented in Appendix A and the mean ratings of the 18 risks on each scale are presented in Appendix B.

To assess the reliability of the data, we constructed two proximity matrices for each task, based upon a random partition of the subjects into two equal groups. The split-half correlations between the matrices were .90, .91, and .87 for the similarity, prediction and evaluation data, respectively.

Correlation Between Tasks. We computed the product-moment correlations between the proximities induced by each task. In accord with the previous analysis, the agreement between the two comparative tasks, similarity and prediction, was fairly high, .76, but their agreement with the (non-comparative) evaluation task was rather low: .36 for similarity and .42 for prediction. Note that in the present design judgments of similarity and conditional predictions were made by different groups of subjects hence the substantial correlation between the responses cannot be attributed to the effect of one task on another. However, the relatively low correlations of evaluation with similarity and prediction may be due to a non-linear relation between the variables. To investigate this possibility, we computed the monotone correlations between the tasks based on the best fitting monotone regression (see, e.g., Kruskal & Wish, 1978). Because this measure is not perfectly symmetric in the two variables, the average of the two coefficients is reported. The non-linear regressions did not change the pattern of results: the correlation between similarity at prediction was .80 whereas evaluation correlated .47 with similarity and .59 with prediction.

Another possible explanation attributes the low correlations to the equal weights assigned to the nine risk dimensions in the calculation of the correlations between the risk profiles. To address this issue, we have used multiple regression to estimate the weights of the nine risk dimensions so as to maximize the correspondence between the observed similarity of a pair of risks and the product-moment correlation between their weighted profiles. That is, we estimated weights, $w_1,\ldots,w_9$, associated with the nine risk dimensions so that the similarity of risks X and Y is as close as possible (in the least-square sense) to $\sum w_i x_i y_i$, where x_i and y_i denote the ratings of risks X and Y on dimension i, in standard scores. The differential weighting of the dimensions had a surprisingly small effect: the correlation between evaluation and similarity was .41 and the correlation between evaluation and prediction was .50. The relatively low agreement between the comparative and the non-comparative tasks therefore cannot be adequately explained by non-linear regressions or by the weighting of the nine scales.

Figure 2 plots, for each pair of risks, their correlation derived from the evaluation data, against their judged similarity. The figure reveals skewed marginal distributions and a triangular joint distribution: highly similar risks are associated with high correlations but dissimilar risks give rise to a wide range of correlations. If we partition the joint distribution at the respective means (indicated by broken lines in Figure 2) we find about twice as many data points in the low-similarity high-correlation cell than in the high-similarity low-correlation cell.

The scatter plot of the predictions against the correlations exhibits a similar pattern, but the joint distribution of similarities and predictions reveals a fairly linear regression.

Insert Figure 2 about here

Rank Agreement. To examine more closely the discrepancies between the measures, we plot in Figure 3, the proximity order of the risks induced by the different tasks. More specifically, we selected one risk (e.g. homicide) as a reference, and ranked the remaining 17 risks by their proximity to the reference risk. Each point in Figure 3 represents the proximity rank of a particular risk, relative to the reference, in two tasks.

Insert Figure 3 about here

Figure 3A shows that evaluation and similarity induce nearly opposite ranking of risks as evinced by the negative correlation between them. When homicide is the reference risk, lightning is its nearest neighbor in the evaluation data, but very distant in the similarity data. In the evaluation data, homicide correlates highly with hazards such as electrocution and lightning; it also correlates highly with the diseases presumably because they are all involuntary, common and tend to claim one life at a time. The similarity ordering reveals a very different pattern: homicide is judged to be most similar to other acts of violence

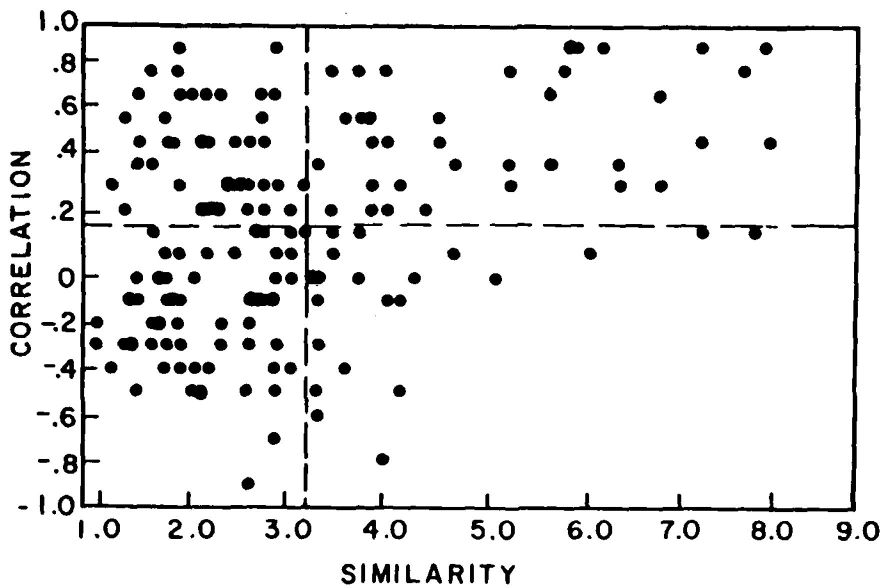


Figure 2. Correlation between risks (derived from the evaluation data) plotted against their judged similarity.

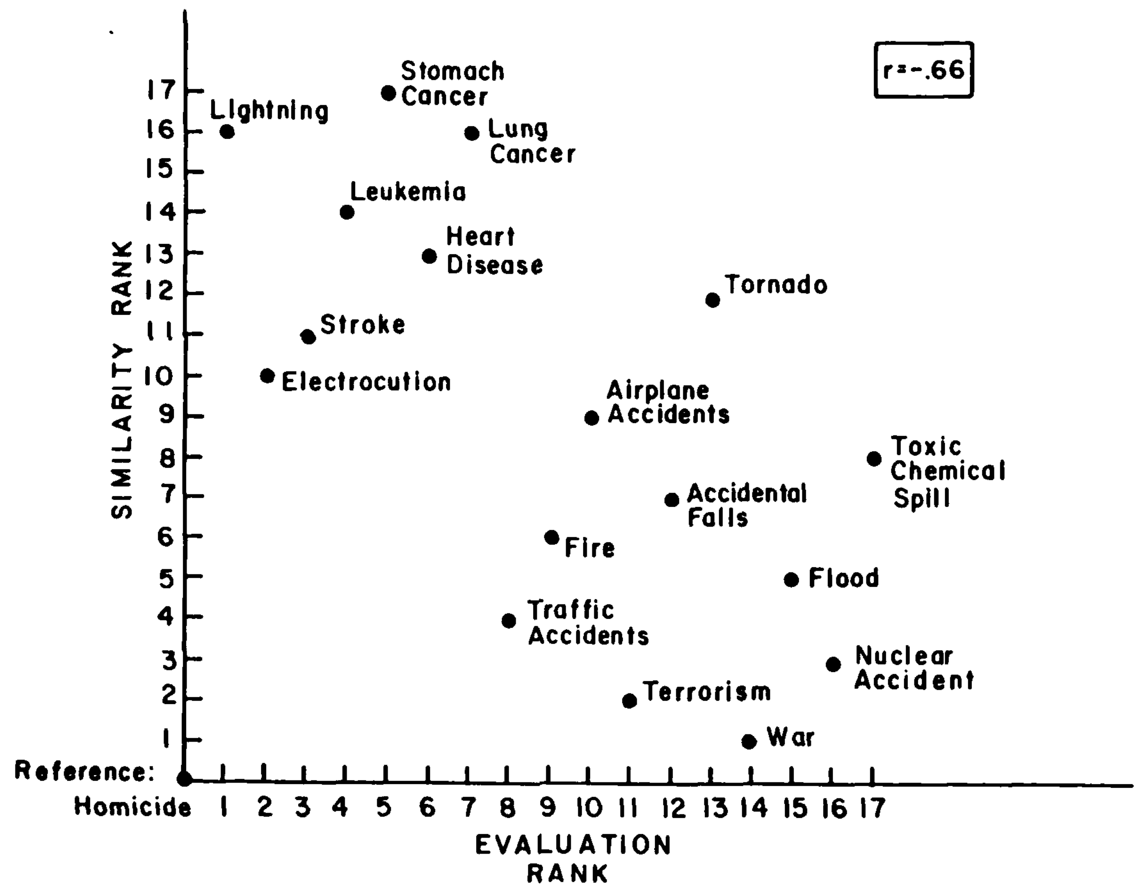


Figure 3A. Rank orders of proximities from two tasks relative to a reference risk. Tasks: similarity and evaluation; Reference: homicide.

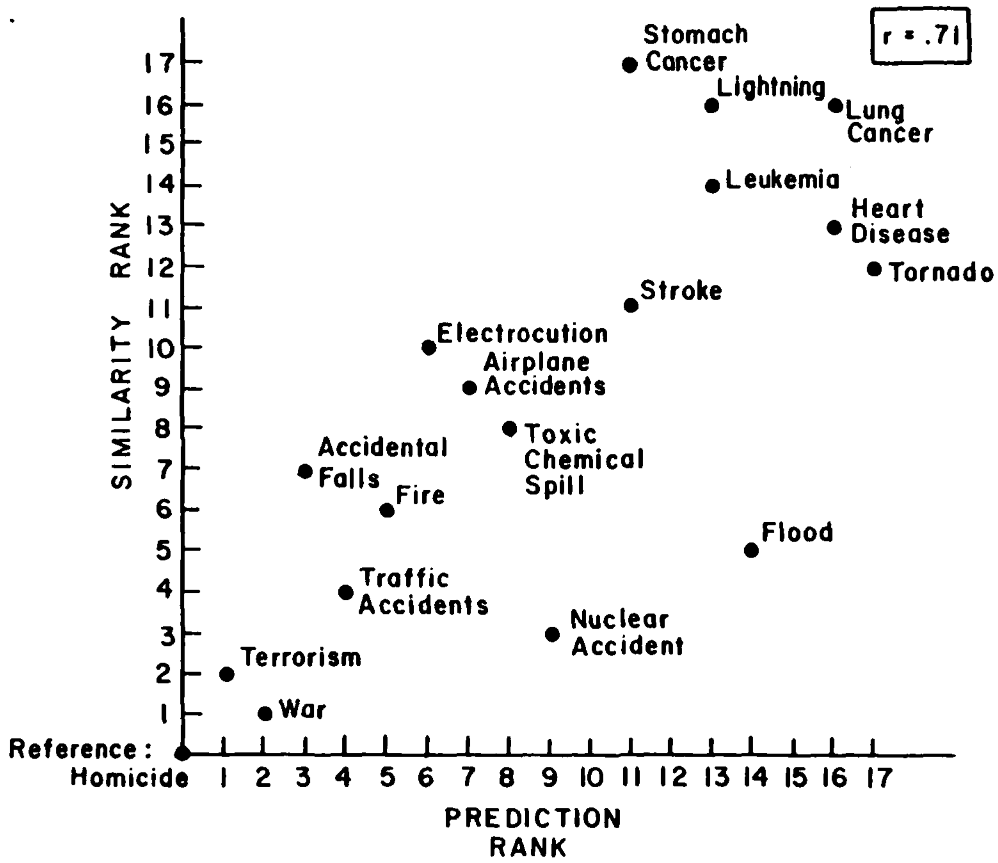


Figure 3B. Rank orders of proximities from two tasks relative to a reference risk. Tasks: similarity and prediction: Reference: homicide.

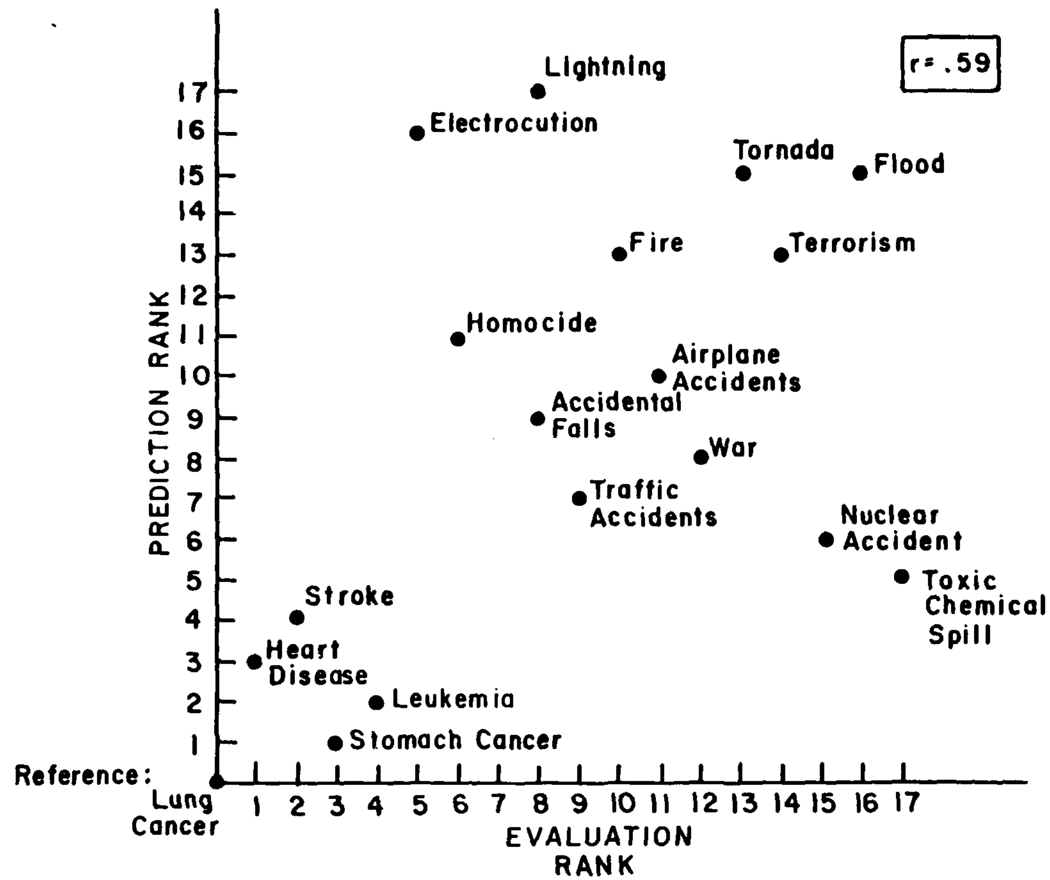


Figure 3C. Rank orders of proximities from two tasks relative to a reference risk. Tasks: prediction and evaluation; Reference: Lung Cancer.

(war, terrorism) as well as to other risks involving human agents (nuclear and traffic accidents). The diseases, which are not caused by a human agent, are least similar to homicide. These inversions of order are responsible for the negative rank-correlation (-.66) between the two measures in Figure 3A. Although the effect is less dramatic for other reference risks, it is evident that judgment of similarity and dimensional evaluation capture different aspects of risk perception.

Figure 3B displays the relation between similarity and prediction, again using homicide as a reference risk. In both tasks homicide is close to the other violent acts and distant from the diseases, and the rank correlation between the measures (.71) is substantial, albeit far from perfect. Figure 3C displays the relation between prediction and evaluation, using lung cancer as a reference risk. The figure shows that the diseases are closest to lung cancer in both orderings but there are substantial and interpretable discrepancies between them. Nuclear accident and toxic chemical spill, which are potential causes of lung cancer, are fairly close to lung cancer in the prediction data and furthest away from it in the evaluation data. This observation suggests that causal considerations loom larger in prediction than in evaluation.

Correspondence Between Data and Models.

Three types of representations are investigated in this paper: Principal component factor analysis (with two and three factors); Ordinal multidimensional scaling (in two and three dimensions); Hierarchical and non-

hierarchical tree models. Two versions of each class of models were applied to the data yielding a total of six representations for each of the three data sets. We first display and discuss the different representations and then describe how well they fit the various data sets.

Insert Figure 4 about here

Tree models. Figure 4 displays the additive tree (ADDTREE, Sattath & Tversky, 1977) constructed for the prediction data. In this representation the risks are the terminal nodes of the tree, and the distance between risks is given by the length of the horizontal part of the path that joins them; the vertical part is included for graphical convenience. A tree representation can be viewed as a hierarchy of clusters; it can also be interpreted in terms of common and unique features. Under the latter interpretation, each (horizontal) segment of the tree corresponds to the measure of the set of features that belong to the objects originating from that segment and to them alone (Tversky, 1977; Tversky & Sattath, 1979). In particular, the terminal segments represent the unique features of each risk and higher order segments represent the features shared by the risks of the corresponding cluster. Figure 4 exhibits a highly distinct and readily interpretable hierarchy of clusters, which are labeled: hazards, accidents, violent acts, technological disasters and diseases.

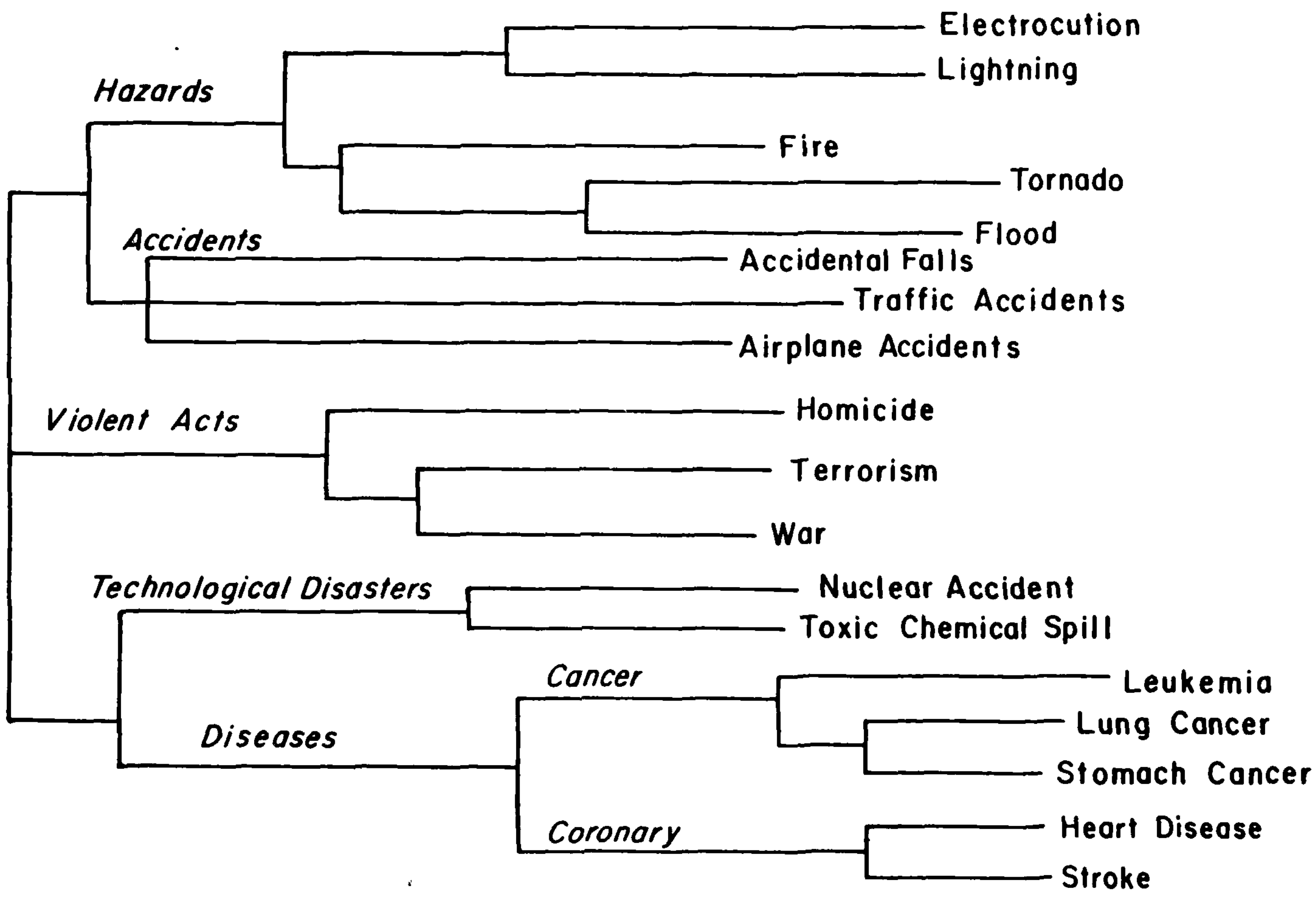
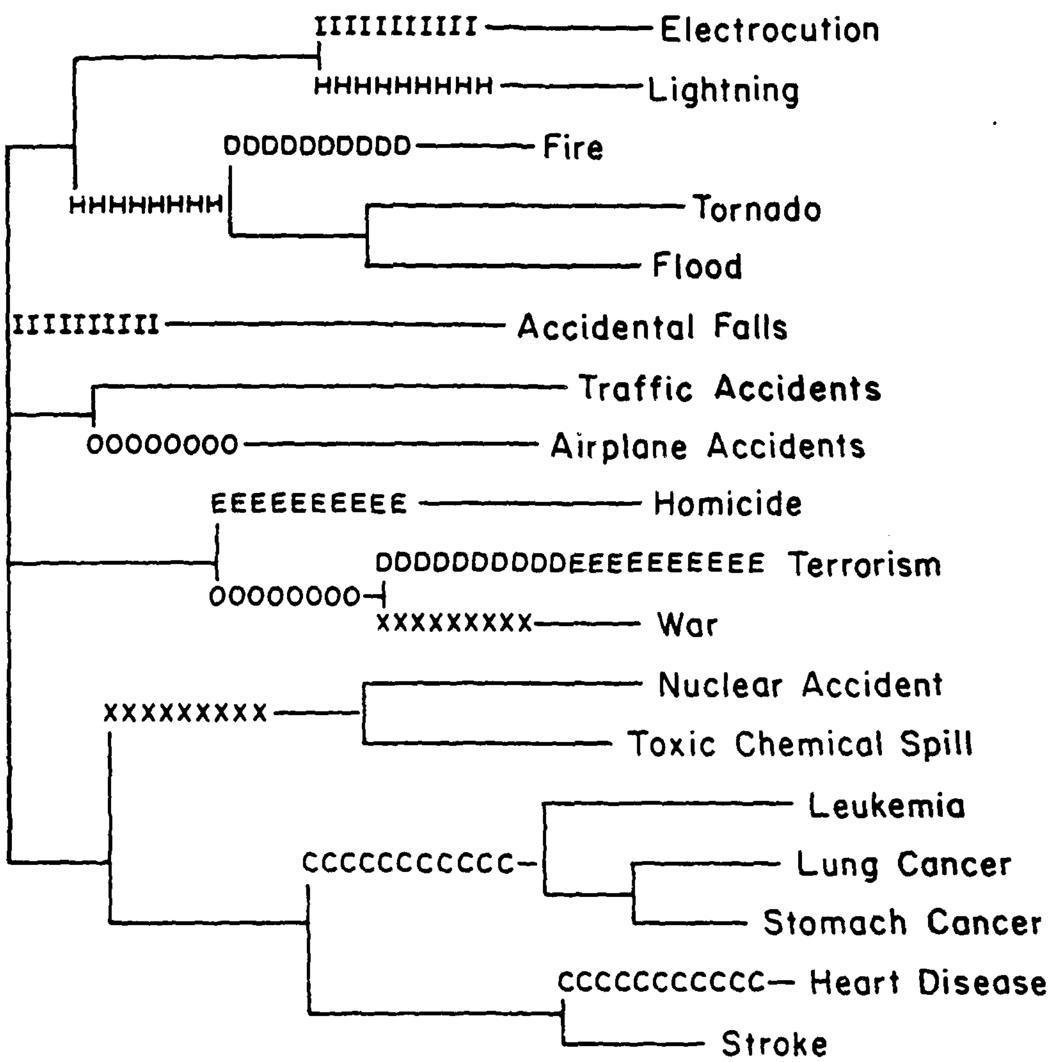


Figure 4. Additive tree (ADDTREE) representation of the prediction data.

Insert Figure 5 about here

As will be shown later, the additive tree model of Figure 4 fits the prediction data quite well. Nevertheless, the results indicate that the clustering of the risks is not entirely hierarchical and there is some evidence for overlapping clusters. This tendency can be observed in the extended tree (EXTREE, Corter & Tversky, Reference Note 1) representation of these data presented in Figure 5. As in the simple additive tree, each (non-terminal) segment defines a cluster that consists of all risks that originate from that segment. An extended tree, however, also includes marked segments, denoted by capital letters. Each marked segment (e.g., X) defines a unique cluster consisting of the risks that include this segment (e.g., War, Nuclear Accident, Toxic Chemical Spill); but this cluster overlaps with the natural clusters of the tree. As in the additive tree, the distance between risks is the measure of their distinctive features, which equals to the (horizontal) length of the path that joins them. In the extended tree, however, the path length excludes any marked segment that appears twice since it represents a common, not a distinctive feature. For example, the distance between War and Nuclear Accident in Figure 5 is given by the horizontal length of the path that joins them excluding the marked segment X that corresponds to features shared by War and Nuclear Acciden'. The (overlapping) clusters defined by the marked segments are listed in Figure 5. For discussion of the extended tree model and the scaling method see Corter and Tversky (Reference Note 1).



I : Electrocution, Accidental Falls.
H: Lightning, Fire, Flood, Tornado.
D: Fire, Terrorism.
O: Airplane Accidents, Terrorism, War.
E: Homicide, Terrorism.
X: War, Nuclear Accident, Toxic Chemical Spill.
C: Leukemia, Lung Cancer, Stomach Cancer, Heart Disease.

Figure 5. Extended tree (EXTREE) representation of the prediction data.

The extended tree of Figure 5 reproduces the major hierarchical clusters that appear in the additive tree of Figure 4. The marked segments, however, introduces a few additional overlapping clusters. For example, the segment H combines Lightning (which is initially joined by Electrocution) with the other natural hazards (Fire, Flood and Tornado). And the segment O clusters Airplane Accidents (which are originally joined by Traffic Accidents) with War and Terrorism.

Insert Figure 6 about here

Multidimensional Scaling. Figure 6 presents the two-dimensional Euclidean solution for the correlations derived from the evaluation data. This representation was constructed using the KYST program (Kruskal, Seery and Young, Reference Note 2) which embeds the risks as points in the plane so that the ordering of the interpoint distances approximates the ordering of their proximities. To facilitate the interpretation of the dimensions we have regressed each of the rating scales against the coordinates of the two-dimensional solution. Five of the nine scales, whose correlation with the solution exceeds .7, are superimposed on the two-dimensional representation (see Kruskal & Wish, 1975, for a description of this procedure). The results suggest two nearly orthogonal dimensions, which roughly correspond to the scales of newness and catastrophic potential. Figure 7 presents a composite representation of the similarity data. The

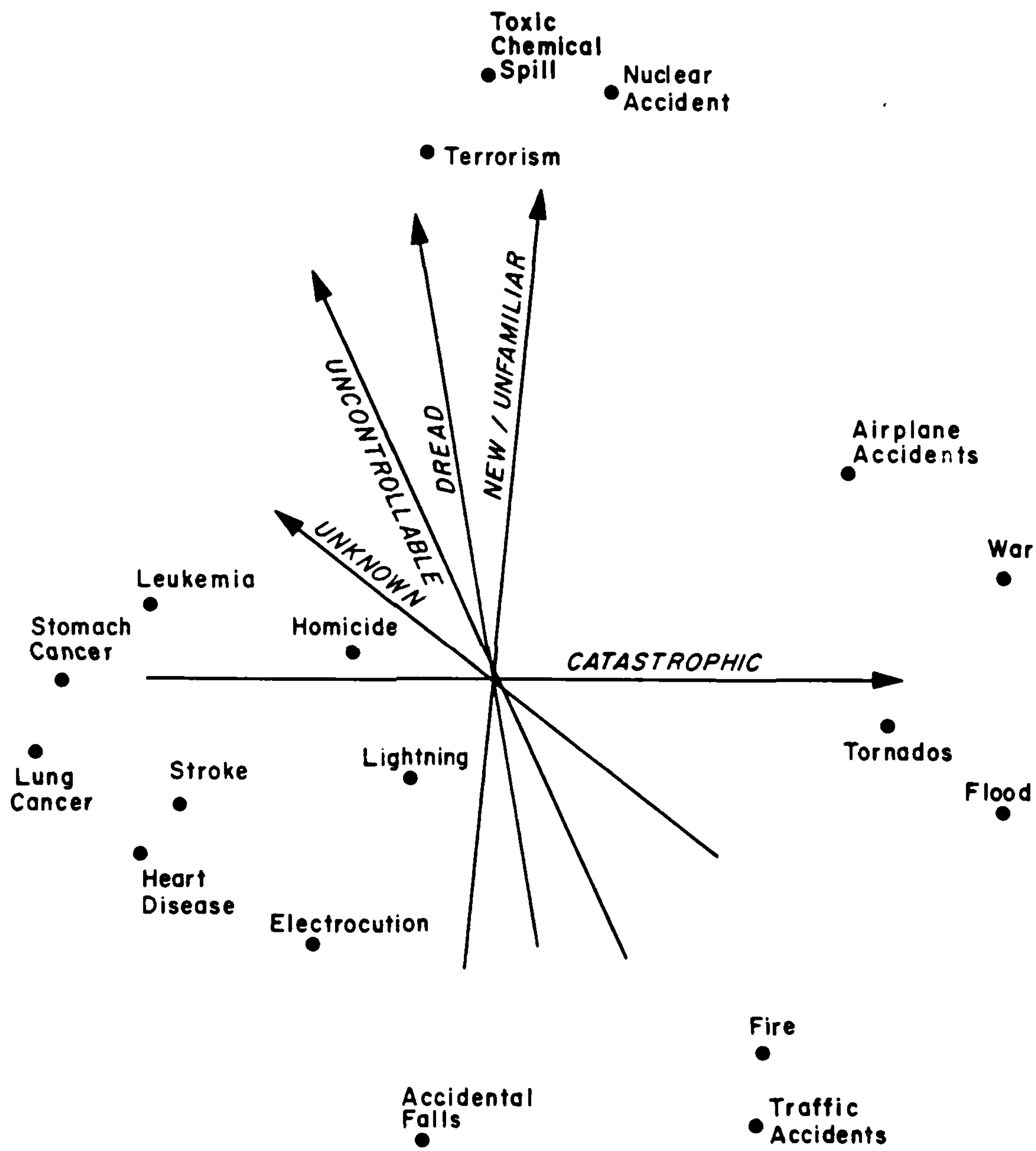


Figure 6. Multidimensional Scaling (KYST) representation of the evaluation data.

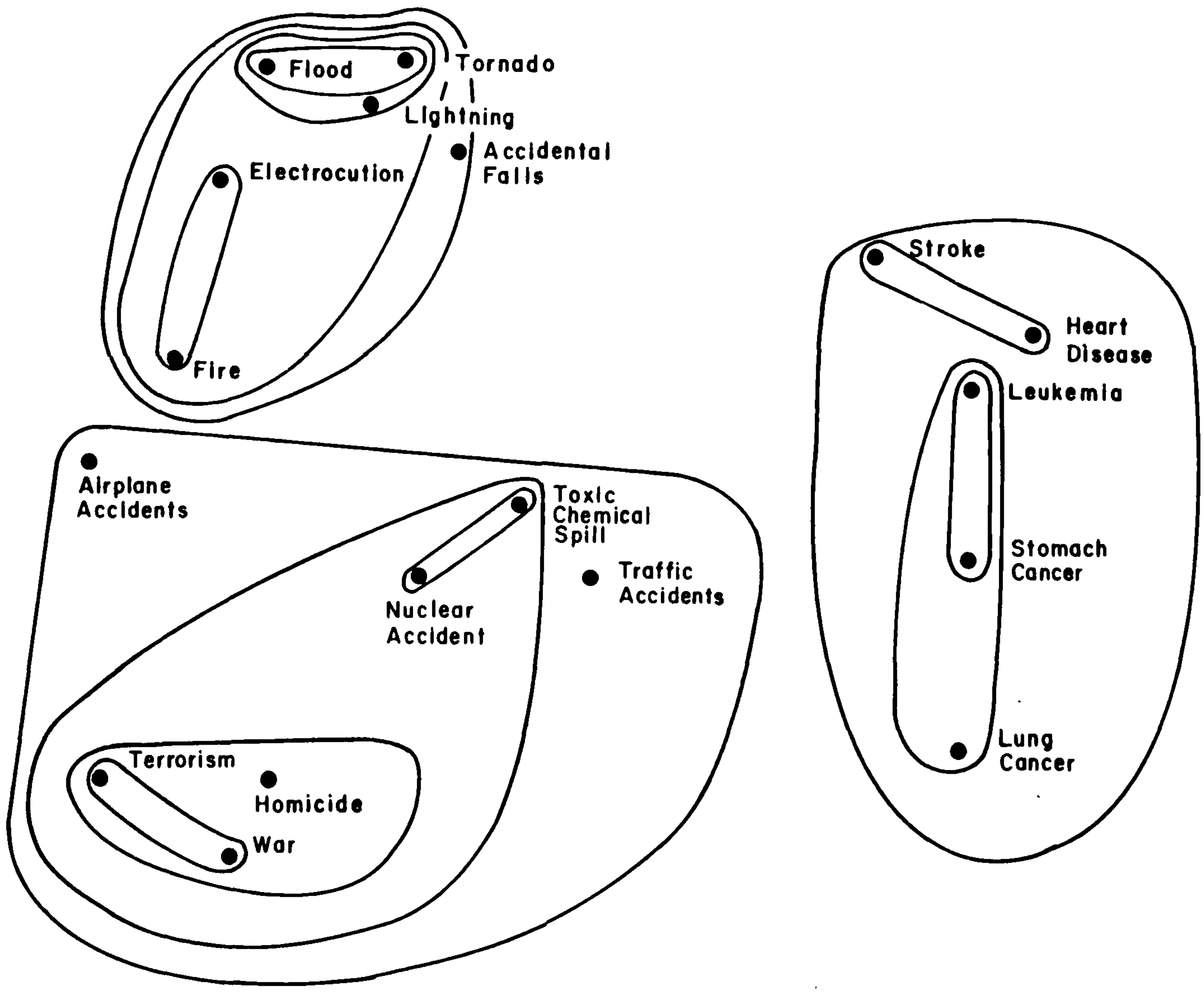
points are arranged in the plane according to the two dimensional KYST solution and the contours describe the clusters obtained by the ADDTREE solution of the same data (see Fillenbaum & Rapoport, 1971; Shepard, 1980).

Insert Figures 7 and 8 about here

Factor Analysis. The factor analytic representation of the intercorrelations between risks, based on the dimensional evaluation data, is presented in Figure 8. The figure displays the loading of each risk on the first and the second factors extracted by a principal component factor analysis (Rummel, 1970). As in multidimensional scaling, the risks appear as points in the plane, but here the proximity between points is expressed by their angle rather than by their Euclidean distance. The two scales with the highest correlations with the data are superimposed on the solution (as in Figure 6) to facilitate the interpretation of the factors.

Goodness of Fit. To compare the solutions to the data, two measures of goodness of fit, r^2_L and r^2_M were used. r^2_L is the squared product moment correlation between the solution and the data or the proportion of linear variance accounted for by the solution. r^2_M is the proportion of variance explained by monotone rather than linear regression of the data against the solution. The values of r^2_L and r^2_M for all six solutions and three data sets are displayed in Table [illegible] To interpret the results note that the two-dimensional models are com-

Figure 7. Composite representation of the similarity data. Points are plotted in a multidimensional (KYST) space, and the solid curves indicate clusters in a tree (ADDTREE) solution.



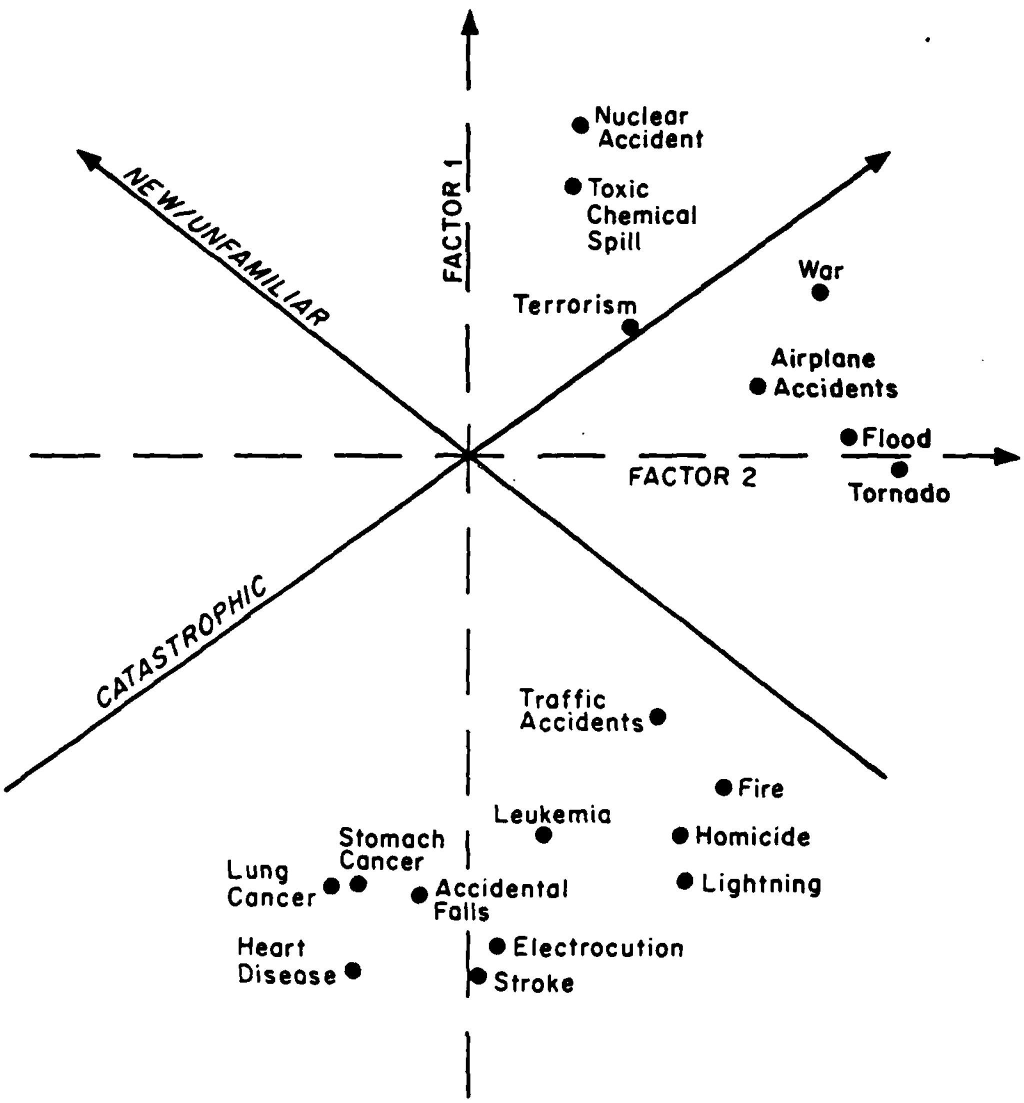


Figure 8. Factor analytic representation of the evaluation data.

parable to the additive tree in terms of the numbers of free parameters, 2n, where n is the number of objects. The three-dimensional models employ more free parameters (3n) than used in the extended trees, where the number of marked segments was bounded by n/2.

A comparison of the columns of Table 2 indicate that, according to both linear and monotone measures, similarity and prediction are better described by trees than by multidimensional scaling or factor analysis. In contrast, the evaluation data is better described by multidimensional scaling than by trees or factor analysis, which yield comparable fit. A comparison of the rows of Table 2 indicate that trees explain prediction better than similarity and evaluation whereas multidimensional scaling and factor analysis explain evaluation better than similarity and prediction. These observations support the hypothesis that trees, or discrete clustering methods, are particularly suited for the representation of similarity and prediction while multidimensional scaling is more appropriate for representing the correlation between profiles. The factor analytic model, which has been commonly applied to the study of risk, appear less successful than either trees or multidimensional scaling.

Insert Table 2 about here

Diagnostic Properties. In addition to the subjective criterion of interpretability and the traditional criteria of goodness-of-fit presented in Table 2, which

Table 2. Percentage of Linear and Monotone Variance Accounted for by the Various Solutions

Data	Index	Tree		MDS		Factor Analysis	
		Addtree	Extree	2 dim.	3 dim.	2 factor	3 factor
Similarity	Linear	74	83	56	64	43	67
	Monotone	83	85	71	81	58	73
Prediction	Linear	89	94	70	85	64	83
	Monotone	92	96	89	94	74	89
Evaluation	Linear	77	84	91	96	74	93
	Monotone	83	87	94	99	80	95

reflect the global correspondence between the solution and the data, it is often instructive to compare alternative representations on the basis of more specific diagnostic properties. Recent work on the representation of proximities has identified several properties of data that can help diagnose whether the data are better described by a tree or by a space. Analytic results (Sattath & Tversky, 1977) and simulations (Pruzansky, Tversky & Carroll, 1982) indicate that trees tend to produce many large distances (between objects from different branches) and fewer short distances (between objects from the same branch). In contrast, spatial models tend to produce more short distances and fewer large distances. As a consequence, trees typically produce negatively skewed distributions of distances while the distribution of the distances between, say, uniformly distributed points in the plane is positively skewed.

Another property that reflects the degree of clustering is based on the comparison of the distances between any three objects. The distances between any three objects can be viewed as a triangle with a long (L), a middle (M) and a short (S) side. Such a triangle is called elongated if the middle side is closer in length to the long than to the short side, or L-M<M-S. Because a tree generally contains more inter-cluster distances than intracluster distances, it is expected to yield a higher percentage of elongated triangles than uniform configuration of points in the plane (Pruzansky et. al., 1982).

The percentage of elongated triangles and the skewness of the distribution of distances (defined by the third central moment divided by the cubed standard deviation) were computed for each of the three data sets. The results agree with the preceding conclusions regarding the appropriateness of spatial versus tree models for different types of data. The similarity and the prediction data exhibited considerable negative skewness (-1.22 and -1.36, respectively) and a substantial percentage of elongated triangles (71% and 73%, respectively). In contrast, the distribution of proximities derived from the evaluation data is positively skewed (.133) and has a lower percentage (64%) of elongated triangles.

The differences between evaluation and the other two tasks may be due to the nature of the task (dimensional evaluation vs. pair comparison) or to the procedures used to extract a proximity measure from the risk profiles. To separate these factors we computed for each pair of risks the correlation between the respective rows in the similarity matrix.[1] The resulting coefficient may be viewed as an indirect measure of proximity that reflects the degree to which the two risks induce the same pattern of similarities over the remaining 16 tasks. It is based on judgments of similarity, but it is computed by an aggregate correlational method. The same procedure was applied to the prediction data.

As might be expected, the correlations between the direct and the indirect measures of similarity and prediction are not high: .40 for similarity and .69 for prediction. The respective monotone coefficients are .51 and .77. However, the correspondence between the new indirect measures and the evaluation data is

even lower. Evaluation correlates .09 with the indirect similarity measure and .12 with the indirect prediction measure. The respective monotone coefficients are .20 and .26. Hence, the use of an indirect correlational procedure did not reduce the discrepancy between evaluation and similarity or prediction.

On the other hand, the indirect measures of similarity and prediction are better fit by factor analysis and multidimensional scaling than the direct measures. For example, the 2-dimensional KYST solution account for 79% of the similarity variance and for 88% of the prediction variance. The corresponding values for the 2-factors solutions are 82% and 94%. Furthermore, unlike the direct measures that are better explained by trees than by dimensional models, the indirect measures are fitted about equally well by trees, by factor analysis and by multidimensional scaling. This observation suggests that the appropriateness of the models depends both on the experimental task and on the method used to define the proximity between objects.

DISCUSSION

The major findings of the present study concern the relation among (i) the nature of the tasks performed by the subjects, (ii) the proximities induced by these tasks and (iii) the formal representations constructed on the basis of these data. We found that the comparative tasks (similarity judgments and conditional predictions) tend to agree with each other, but the agreement between these data and the dimensional evaluations is rather low. Furthermore, the com-

parative tasks are better described in terms of discrete feature models (e.g., ADDTREE and EXTREE) whereas the evaluation data are better accounted for by multidimensional scaling.

In order to interpret and evaluate a formal representation of some psychological domain, such as risk perception, two types of invariance should be examined: item invariance and task invariance. Item invariance refers to the degree to which the representation is affected by changes in the selection of items from the relevant domain. Task invariance refers to the degree to which the representation is influenced by the task. In this section we address these issues in turn and discuss their implications to the study of risk perception.

The most extensive program of research on the perception of risk has been conducted by Slovic, Fischhoff, Lichtenstein and their collaborators at Decision Research in Eugene, Oregon (Fischhoff, et al. 1978, 1981; Slovic et al. 1980, 1981, 1983). These investigators introduced the dimensional evaluation task used in the present study and constructed factor analytic solutions for several sets of risks based on the ratings of lay people and experts. The risks used in these studies included primarily activities (e.g., smoking), substances (e.g., food coloring), and technologies (e.g., X-rays). The authors found that two or three factors accounted for about 80% of the variance in their studies. They have labeled the first factor "unknown risk", the second factor "dread risk" and the third factor "degree of exposure"(Slovic et al. 1983). The factor analytic representation was remarkably stable: essentially the same factor structure was obtained for several

groups of subjects and for different sets of scales and risks, of the same general type.

The risks used in the Oregon studies differ from the present risks in several respects. First, the former included activities (e.g., skiing, smoking, hunting) and products (e.g., food preservatives, pesticides, vaccinations) that generate risk as a by-product and are not normally thought of as causes of death. Second, the Oregon studies did not include diseases (e.g., stomach cancer, stroke) or natural hazards (lightning, tornado, flood). Nevertheless, more than half of our items were included in the Oregon studies, often in a more specific form. The effect of the risk set can be observed in Table 3, which displays the correlations, across risks, between the nine rating scales. The results of Fischhoff et al. (1978) appear above the diagonals and the results of the present study appear below the diagonal.

Insert Table 3 about here

Table 3 reveals substantial differences between the correlational structures. The average absolute correlations is .51 in the Oregon study and only .30 in our study. If we focus on the intercorrelations between the first five scales the respective averages are .73 and .22. Evidently, the replacement of technologies by diseases and natural hazards reduces the dependence among the scales. Indeed, a two-factor solution fits the Oregon data better than the present evaluation data

Table 3. Product-moment correlations between nine rating scales, across risks. Data from Fischhoff et al. (1978) appear above the diagonal; evaluation data from the present study appear below the diagonal.

Scale	1	2	3	4	5	6	7	8	9
1. Involuntary		.54	.83	.75	.76	.65	.55	.55	.06
2. Effect Delayed	.06		.78	.68	.42	.63	.16	.25	-.22
3. Not known to exposed	.73	.04		.87	.63	.78	.35	.31	-.22
4. Not known to science	.44	-.21	.32		.60	.83	.35	.46	-.14
5. Not Controllable	.41	.14	.38	.52		.64	.63	.64	.24
6. New/Unfamiliar	-.04	.31	.23	.29	.43		.46	.53	-.05
7. Catastrophic	-.02	.29	-.25	.61	.46	.13		.60	.46
8. Dread	-.06	.28	-.06	.42	.61	.57	.47		.63
9. Certainly Fatal	-.24	.20	-.14	-.26	.26	.16	-.18	.57	

and the resulting factor structures are quite different. Although much discussion about the management and the regulation of risk has focused on technologies and activities (Fischhoff et al. 1981), many of the risks that worry people in everyday life are not usually conceived in this way. A comprehensive representation of the perception of risk should encompass, besides technologies and activities, natural hazards and diseases along with economic and psychological risks, such as bankruptcy or divorce (Johnson & Tversky, 1983).

The evaluation of a formal representation of psychological data should consider not only variations in stimuli (e.g., risks) but also variations in the response or the task performed by the subject. As the present study show, different tasks give rise to systematically different proximities between risks, which in turn suggest different formal representations. It is instructive, therefore, to examine the strengths and weaknesses of the tasks used on the present study and explore their relevance to the study of risk perception.

The dimensional evaluation procedure has several advantages. First, it is easy to use even with a large set of stimuli that require a prohibitive number of paired comparisons. Slovic et al. (1983) have used this method with as many as 90 hazards. Second, it structures the subjects' task and focus their attention on pertinent attributes of the stimuli, reducing the impact of irrelevant considerations. The evaluation task, however, has its limitations: the scales are typically confined to global dimensions that apply to all risks, hence one is likely to overlook local features that apply only to a small subset of objects. The data

reported in this article suggest certain aspects of risk perception are not captured by dimensional evaluation. For example, Figure 3A shows that homicide and war are perceived as similar although the correlation between their ratings is very low.

Similarity judgments provide a more direct measure of the proximity between risks in which the identification and the weighting of the relevant attributes are performed by the subject. This is both a strength and a weakness: the subject is not constrained by the scales selected by the investigator but the judgments are susceptible to various effects that may or may not be relevant to the study of risk. Which measure of proximity, if any, is relevant to risk analysis depends on the purpose of the investigation. Slovic et.al. (1981) showed that lay attitudes regarding risk policy are closely related to the dread factor derived from the dimensional evaluation data. The higher the loading of an activity on the dread factor, the more people want its risk reduced and the more they want to see it regulated. On the other hand, we have found that conditional prediction (which measures the perceived covariation between risks) correlates highly with similarity but not with evaluation. This observation suggests that similarity may play an important role in predicting people's responses to new risks or to new evidence about risk. The public reaction to the Tylenol poisoning may be a case in point. The incident appeared to provoke fears concerning over-the-counter drugs, but not other products (e.g., foods) which could easily suffer from tampering. And the similarity between nuclear power and nuclear warfare appears to fuel

much of the heated public debate about the acceptability of nuclear power plants.

It is evident that any single task (e.g., prediction, evaluation, similarity) and any formal representation (e.g., trees, spaces) derived from such data do not adequately capture the complexity and richness of people's conception of risk. Some of the limitations of specific tasks and models can be partly reduced by a multi-task, multi-model approach in which a domain is explored by different tasks that are analyzed by different models. The application of this approach to the representation of risks suggests that the combination of psychometric methods with cognitive task analysis offers a viable methodology for the study of complex conceptual domains.

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Footnotes

1. This analysis has been suggested by George Furnas.

Appendix A

Mean conditional prediction (above the diagonal) and similarity ratings (below the diagonal) for all pairs of risks.

	AF	AA	Elec.	Fire	Flood	HD	Homi.	Leuk.	Ligh.	LC	NA	SC	Stroke	Terr.	Torn.	TCS	TA	War
Accidental Falls		33	44	33	26	16	30	9	31	8	18	10	20	18	24	18	40	25
Airplane Accidents	2.4		14	41	29	9	15	7	29	7	23	10	16	33	24	28	40	39
Electrocution	3.1	3.0		44	30	9	17	5	60	4	14	6	18	12	19	18	14	11
Fire	4.6	3.0	7.0		53	6	24	5	53	5	23	11	14	40	49	23	39	26
Flood	3.8	4.2	4.1	3.0		6	7	5	49	5	18	7	13	7	65	19	20	17
Heart Disease	2.5	1.9	2.4	1.7	1.5		7	58	7	62	15	59	78	6	7	16	10	11
Homicide	3.6	3.1	2.6	3.9	4.7	2.5		8	8	7	14	13	11	63	6	14	29	44
Leukemia	2.9	2.1	2.1	2.6	3.5	5.6	2.3		7	71	17	72	41	5	6	25	6	4
Lightning	3.8	4.2	6.7	6.2	6.7	4.2	2.0	1.9		3	20	5	5	10	48	19	15	8
Lung Cancer	2.5	2.1	1.7	2.7	2.3	3.1	2.0	3.9	2.2		24	86	53	5	5	23	9	8
Nuclear Accident	2.9	3.5	3.5	3.5	3.5	1.9	6.0	3.1	3.5	2.0		30	17	26	12	67	12	14
Stomach Cancer	1.8	2.0	2.1	2.3	1.8	5.9	1.8	6.2	2.9	5.7	3.1		37	7	7	35	17	9
Stroke	4.0	2.3	2.3	2.8	2.1	7.0	2.5	5.2	3.7	5.9	1.7	2.9		10	12	24	24	11
Terrorism	2.3	4.3	3.0	3.7	3.0	1.8	6.2	1.6	3.0	2.3	2.9	1.9	2.9		6	15	18	65
Tornados	3.2	3.4	3.9	4.6	7.7	1.9	2.5	2.0	7.6	1.4	3.7	2.1	5.1	2.9		15	15	5
Toxic Chemical Spill	3.1	3.6	3.3	4.3	3.1	2.4	3.2	3.3	3.5	3.0	7.3	3.0	2.6	3.6	4.5		18	30
Traffic Accidents	5.2	5.3	3.0	4.2	2.8	3.3	4.7	2.3	2.9	3.3	3.2	2.2	4.3	2.9	2.5	4.2		12
War	2.5	3.8	2.9	3.9	2.7	2.0	7.0	2.6	3.0	2.6	5.7	2.1	2.2	7.5	2.2	2.2	3.0	

Appendix B

Mean Ratings of 18 risks on nine Evaluation Scales

Risk	Not known to Science	Not Known to those exposed	New/ Unfamiliar	Effect Delayed	Involuntary	Not Controllable	Certainly Fatal	Dread	Catastrophic
Accidental Falls	3.59	4.56	2.09	3.37	4.52	2.85	2.91	2.57	1.51
Airplane Accidents	2.82	3.56	3.41	2.74	3.27	5.28	5.66	4.77	5.60
Electrocution	3.25	3.79	3.43	2.80	4.83	3.43	4.83	3.57	1.54
Fire	3.51	3.71	2.09	3.17	5.13	3.03	4.19	3.80	4.31
Flood	4.22	4.05	1.98	3.42	5.77	4.60	3.52	3.44	5.72
Heart Disease	2.67	3.71	2.72	4.94	4.30	3.70	5.33	3.82	1.54
Homicide	4.06	4.82	2.43	2.62	5.55	4.88	6.44	5.00	2.43
Leukemia	2.94	4.56	3.26	5.17	6.13	5.72	5.44	4.44	1.56
Lightning	4.19	4.69	2.20	3.00	5.80	5.29	4.75	3.00	1.78
Lung Cancer	2.71	3.30	3.06	5.25	3.75	3.82	5.72	4.47	1.78
Nuclear Accident	5.19	4.28	5.49	4.20	4.66	5.82	5.41	6.02	5.96
Stomach Cancer	3.03	4.33	3.40	5.34	4.72	4.54	4.94	4.29	1.59
Stroke	2.42	4.05	2.80	4.20	4.36	4.22	5.22	4.35	1.56
Terrorism	5.70	4.38	4.40	4.00	5.75	5.64	4.19	5.32	4.28
Tornado	4.09	4.23	2.00	3.42	5.94	5.48	3.75	3.66	5.40
Toxic Chemical Spill	4.48	4.64	5.23	4.30	5.36	5.48	4.08	4.90	4.96
Traffic Accidents	3.20	3.46	3.06	2.54	3.31	3.79	4.17	3.36	3.59
War	4.73	3.20	1.65	3.60	4.14	5.03	5.22	5.54	6.81

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